

Optimal Site Selection for Military Land Management

R.M. Wallace¹

Abstract

Site selection procedures have improved rapidly with the acceptance of GIS technologies that can quickly evaluate the properties of thousands of potential sites. However, when more than a single parcel of land is required or when the certainty of the decision requires a more deliberate selection procedure, a systematic methodology is needed to analyze multiple scenarios and select an optimal or near-optimal solution.

This need is especially true for military installations where unique land uses require calculated decision making that reflect more than “best judgment” decisions. Examples of these unique land uses include the location of hazardous storage facilities and the location of live-fire exercises. These distinctive activities are further complicated by the desire to increase the level of readiness by conducting additional training exercises on limited resources. An additional factor influencing the location of activities on military installations is that many of these sites have become prime habitat for threatened and endangered species.

This paper describes the use of a site selection model to identify and evaluate and generate optimal regions with specific shape properties. In addition a heuristic algorithm that uses the “greedy” principle is applied to find solution regions with specific shape properties and non-inferior cost values. A case study using the model will be used to identify least cost areas for training activities on the Fort Hood military reservation.

¹ U.S. Army Engineer Research & Development Center, Coastal and Hydraulics Laboratory, 3909 Halls Ferry Road, Vicksburg, MS 39180; (601) 634-4410; Robert.M.Wallace@erdc.usace.army.mil

Introduction

Military land managers face severe challenges in deciding how best to manage the land under their jurisdiction. These include unusual activities that may prohibit standard restoration activities, large geographical areas with mixed urban and training land use, and the presence of sensitive or endangered species that must be protected. Furthermore, as the need for military training increases, these competing demands on the land may require a site selection method that allows the land manager to select optimal locations for various activities.

Traditional GIS analysis techniques have focused on combining multiple data layers to identify regions with suitable properties for specific activities. This approach lacks the ability to identify the “best” among several potential sites. When a more exhaustive selection approach is appropriate, such as selecting sites for military activities, additional analysis techniques are required. This is especially true when multiple parcels of land are required, when a raster dataset is being evaluated or when the certainty of the decision requires a more deliberate selection procedure is needed to analyze multiple scenarios and select an optimal or near-optimal solution.

Spatial optimization provides the ability to model complex environmental and managerial processes using GIS algorithms with traditional combinatorial optimization algorithms. This combined methodology has been used to methodically analyze large spatial problems to find optimal or non-inferior solutions. Spatial optimization evaluates multiple solutions to a spatial problem allowing the algorithm to systematically find the best solution for a specific objective function within a set of pre-specified constraints. This technique extends and enhances traditional GIS spatial analysis by finding optimal or non-inferior solutions from a much larger set of feasible answers. Spatial optimization has been successfully employed to evaluate numerous types of problems including location-allocation modeling, land-use planning, and environmental resource management.

A subset of the general spatial optimization problem is the region aggregation problem (also known as land acquisition or site search). If a particular region is thought of as a continuous surface of non-overlapping parcels, then the region aggregation problem combines individual parcels into a contiguous and well-formed subset that meets the objectives of the user. Region aggregation modeling was applied by Lin and Kao (1999) on a vector data set and Yen (1999) on a raster data set to find the optimal location for a landfill. Brookes (1997) used a type of region aggregation modeling to locate optimal sites for habitat restoration on a raster data set.

This paper presents an advanced formulation of the region aggregation model that can be used to find optimal locations for activities and facilities that require additional justification for their location such as those found on military sites. Furthermore, a parallel search heuristic is demonstrated that can solve the region aggregation model for significantly sized data fields represented by either the raster or vector data model.

Optimal Region Aggregation

Advanced region aggregation model formulation

The region aggregation problem is classed as a binary discrete combinatorial mathematics problem. The mathematical model for the region aggregation problem is designed to find the lowest cost collection or grouping of polygons that satisfies a set of constraints. The size and shape of the solution region is governed by these constraints. The model formulation used in this research was derived primarily from the Lin and Kao (1997) model formulation. The mathematical model used in this research is presented as Equation 1.

$$\min Z = \sum_{i \in R} C_i \quad (1)$$

Subject To:

$$\sum_{i \in R} A_i \geq A_r \quad (1a)$$

$$\text{comp}[R] \leq \text{comp}_r \quad (1b)$$

$$\text{conv}[R] \geq \text{conv}_r \quad (1c)$$

$$\text{avar}[R] \leq \text{avar}_r \quad (1d)$$

$$\theta_{\min} \leq \theta[R] \leq \theta_{\max} \quad (1e)$$

$$\text{aspect}_{\min} \leq \text{aspect}[R] \leq \text{aspect}_{\max} \quad (1f)$$

$$R \in S$$

Where:

Z = Total cost to acquire polygon set R

S = Index set of non - overlapping polygons

R = Index set of acquired polygons, $R \subseteq S$

C_i = Cost to acquire polygon i

A_i = Area of polygon i

A_r = Area required for region R

W_j = Weight value for environmental suitability factor j

$\text{avar}[R]$ = Elliptic variance of region R

avar_r = Elliptic variance required for region R

$\text{conv}[R]$ = Convexity of region R

conv_r = Convexity required for region R

$\text{comp}[R]$ = Compactness of region R

comp_r = Compactness required for region R

$\theta[R]$ = Orientation of region R

θ_{\max} = Maximum allowable orientation of region R

θ_{\min} = Minimum allowable orientation of region R

$\text{aspect}[R]$ = Aspect ratio of region R

aspect_{\max} = Maximum allowable aspect ratio of region R

$aspect_{\min}$ = Minimum allowable aspect ratio of region R

The objective of this model is to find the minimum cost subset, R , from a set of contiguous cells or polygons, S , while also satisfying a series of six constraints. The subset must contain at least one polygon but needs only as many polygons as required to satisfy the constraints. The costs for each individual polygon can either be the monetary costs for the parcel of land or can represent some other factor such as environmental suitability. In the case where there are multiple physical attributes, a GIS overlay technique can be used to combine the layers into a single cost layer.

Modeling Constraints

Constraints 1a-1f from Equation 1 are used to insure that the specific objectives of any facility location exercise are met. Without these constraints the region aggregation model degenerates into the more general knapsack problem from classic operations research. The constraint set applied in this research includes the ability to specify the shape of the desired region. This allows the model to find regions that are non-circular and with specific orientation and aspect ratios.

The constraints used in this example are area, compactness, convexity, orientation, aspect ratio, and area variance. Compactness is defined as the ratio between the square of the perimeter of the region and its area (P^2/A). Convexity is defined as the ratio between the length of the convex hull of the region and its perimeter (C_{hull}/P). The orientation and aspect ratio are computed using the first area moments of inertia of the planar polygon region. The orientation is defined as the azimuth of the principle moment and the aspect ratio is defined as the ratio between the magnitude of the primary moment and the magnitude of the secondary moment. The area variance is defined as the non-overlapping area resulting from the spatial union function between the polygon region and a reference ellipse. The reference ellipse is centered at the centroid of the polygon region, has an eccentricity based on aspect ratio of the polygon region and an equivalent orientation as the polygon region.

These constraints were derived from the work of Peura and Iivarinen (1997) who demonstrated that five simple shape parameters could be used to describe a planar polygon region. The equations describing these parameters were transformed by Wallace (2002) from a statistical representation used in the original work to geometric representation using Green's theorem.

Region Building Heuristic Algorithm

A region building algorithm was developed to solve the region aggregation problem described above. The algorithm builds, from a seed polygon, a region with minimum cost and shape parameters that satisfy the shape constraints discussed in the previous section. The algorithm selects from the neighborhood of adjacent polygons, the single polygon that has the best cost and shape properties. The algorithm uses a "greedy" principle that only evaluates the adjacent polygons. The algorithm continues to add adjacent polygons, building the region using a procedure based on the shape

properties of the combined region, until the area constraint is satisfied. Constraint 1a is used as the stopping criteria. If the final region satisfies the shape constraints, the solution for that seed polygon is part of the candidate set. After all seed polygons are evaluated, the candidate set is searched to find the lowest cost solution. This algorithm works equally well with or vector data sets. This algorithm is described in greater detail by the author in Wallace (2002).

Site Selection Example

A demonstration of this algorithm is presented in which a fictional land manager wants to locate the optimal location for a live fire exercise that minimizes the cost for restoring the land to its original location. The prevailing winds in the area dictate that the live-fire exercise should be oriented such that any brush fires started by inadvertent explosions can more easily be contained. The attribute layers required to optimally locate this training activity include: (1) the soils types, (2) the vegetation types, (3) the presence of threatened or endangered species, (4) the proximity to exiting roads, (5) the proximity to streams and (6) the proximity to existing training areas.

The separate layers are combined into a single cost data layer using the standard GIS overlay procedure. The unit restoration cost for each combined polygons was computed using equation 2.

$$C_{unit} = C_{roads} + C_{streams} + C_{tes} + C_{veg} + C_{training} + C_{soils}$$

$$C_{polygon} = C_{unit} * Area$$

Equation 2

The resultant data set shows the restoration costs for the entire range under consideration and is shown in Figure 1.

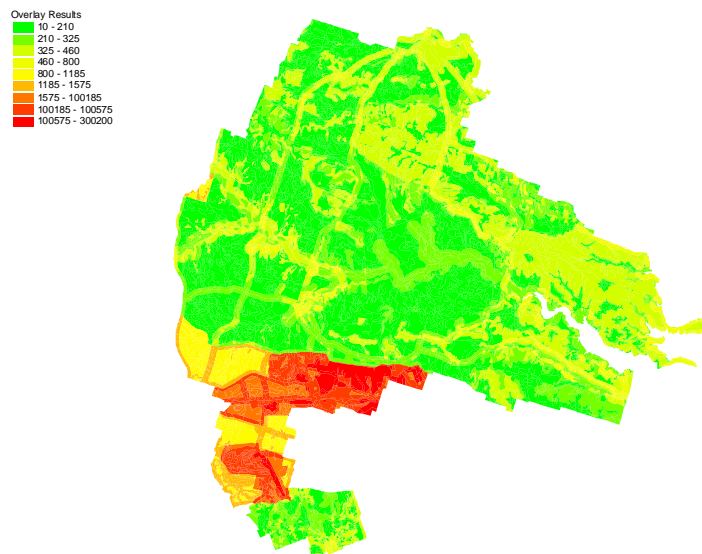


Figure 1 – Map showing the resulting polygons and associated unit costs after polygon overlay operation. The resultant polygon data set included more than 18,000 polygons.

The target shape for this exercise is an elongated ellipse whose attributes are shown in Table 1.

Table 1 – The shape target for this test is presented in this table.

Shape Properties	
θ°	100
aspect	3.0
area	1.20E+6

Two separate constraint sets were used in this example to demonstrate how the constraints impact the shape and cost of the resultant region. These constraint sets are shown in Table 2.

Table 2 – The shape quality constraints are presented in this table. Set one is less restrictive while set two is more restrictive

Constraint Set	Shape Constraints		Constraint Set	Shape Constraints	
1	θ°	± 10	2	θ°	± 5
	aspect	± 0.5		aspect	± 0.2
	avar _r	0.01		avar _r	0.002
	comp _r	100		comp _r	50
	conv _r	0.5		conv _r	0.8

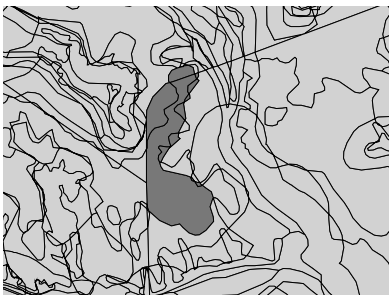
The analysis sets created by combining the shape target and the constraint sets are shown in Table 3.

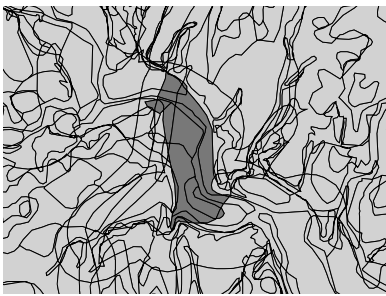
Table 3 – The analysis sets created by combining the shape constraints and the shape target are presented in this table.

Set	Shape Constraints		Set	Shape Constraints	
1	θ°	100 ± 10	2	θ°	100 ± 5
	Aspect	3.0 ± 0.5		Aspect	3.0 ± 0.2
	A _r	1.20E+6		A _r	1.20E+6
	avar _r	0.01		avar _r	0.002
	comp _r	100		comp _r	50
	conv _r	0.5		conv _r	0.8

Table 4 shows the shape and cost properties, the shape constraints and the solution image for the solutions generated in this test. The results of this test indicate that the algorithm finds regions with non-inferior cost values where the size and shape of the solution region is very close in to the desired size and shape.

Table 4 – The test results showing the shape constraints, the numeric results and an image of the solution region are presented in this table. The solution regions are shown in dark gray.

Set	Shape Constraints		Numeric Results		Image
1	θ°	100 ± 10	cost	1.797E+05	
	aspect	3.0 ± 0.5	θ°	95.3	
	A _r	1.20E+6	aspect	3.02	
	avar _r	0.01	A	1.218E+06	
	comp _r	100	avar	0.00582	
	conv _r	0.5	comp	35.1	
			conv	0.867	

Set	Shape Constraints		Numeric Results		Image
2	θ°	100 ± 5	cost	4.712E+05	
	aspect	3.0 ± 0.2	θ°	101.7	
	A_r	$1.20E+6$	aspect	3.14	
	avar _r	0.002	area	1.207E+06	
	comp _r	50	avar	0.00128	
	conv _r	0.8	comp	32.4	
			conv	0.871	

Algorithm Efficiency

Each test case produced a number of solutions that satisfied the constraints. For the relaxed constraints, a candidate solution was generated for 72.21% of the seed polygons. For the more restrictive shape constraints, a candidate solution was generated for only .13% of the seed polygons. Care must be taken to not over-constrain the model, but these results indicate that the region building algorithm does a good job of building regions with that satisfy the shape properties.

The test also demonstrates the trade-off between strict shape compliance and cost. The solution generated with the more restrictive shape constraints was significantly more costly than the solution generated with less restrictive shape constraints. In this case the penalty for the “better” shape was an increase in costs of 260%. This test satisfactorily demonstrates the ability of the mathematical model and solution algorithm to find regions with specific shape properties.

Conclusion

The advent of GIS technology has increased the capability of land managers to find appropriate locations for specific applications and activities. Spatial optimization methodologies increase the value of standard GIS analysis by systematically searching through a large number of possible solutions to find the best or optimal. This is particularly useful when selecting site locations for activities or facilities that are subject to significant risks such as at military installations. The region aggregation model and solution heuristic presented in this paper have demonstrated the ability to find the optimal location for a complicated vector data set.

References

- Brookes, C.J. (1997). “A parameterized region-growing programme for site allocation on raster suitability maps.” *International Journal of Geographical Information Science*, Taylor & Francis, 11(4), 375–396.
- Lin, H.Y. and Kao, J.J. (1999). “Enhanced spatial model for landfill siting analysis.” *Journal of Environmental Engineering*, ASCE, 125(9), 845–851.
- Peura, M. and Iivarinen, J. (1997). “Efficiency of simple shape descriptors.” *3rd International Workshop on Visual Form*. Capri, Italy, May 28–30 1997.

- Steege, C. (1996). "On the calculation of arbitrary moments of polygons." Technical University of Munich, Germany. Technical Report FGBV-96-05.
- Wallace, R.M. (2002). "Enhanced region aggregation modeling using improved shape constraints." Ph.D. Dissertation, Department of Civil and Environmental Engineering, Purdue University, West Lafayette, IN.
- Yen, C. (1998). "A quantitative method for engineering site selection." Masters Thesis, Department of Civil and Environmental Engineering Purdue University, West Lafayette, IN.